Sniffer: Origin Tracing and Detecting of LLMs

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Abstract

The extraordinary performance of large language models (LLMs) heightens the importance of detecting whether the context is generated by an AI system. More importantly, while more and more companies and institutions release their LLMs, the origin can be hard to trace. Since LLMs are heading towards the time of AGI, similar to the origin tracing in anthropology, it is of great importance to trace the origin of LLMs. In this paper, we first raise the concern of the origin tracing of LLMs and propose an effective method to trace and detect AI-generated contexts. We introduce a novel algorithm that leverages the contrastive features between LLMs and extracts model-wise features to trace the text origins. Our proposed method works under both white-box and black-box settings therefore can be widely generalized to detect various LLMs.(e.g. can be generalized to detect GPT-3 models without the GPT-3 models). We construct extensive experiments to examine whether we can trace the origins of given texts. We provide valuable observations based on the experimental results, such as the difficulty level of AI origin tracing, and the AI origin similarities, and call for ethical concerns of LLM providers. We are releasing all codes and data as a toolkit and benchmark for future AI origin tracing and detecting studies. [1]

1 Introduction

Using LLMs such as ChatGPT and GPT4 (OpenAI, 2023) for various daily routines and copilot in work is becoming a new trend that draws worldwide attention not only in the machine learning community. Starting from GPT (Radford et al., 2018) and BERT (Devlin et al., 2018), pre-trained models have developed for several years, and trustworthy and security concerns have been constantly discussed (Bai et al., 2022). The performances of LLMs are sensational, therefore, the usage of LLMs should be strictly supervised by users as well as service providers. One trend in ensuring the safety of LLMs is to build detection tools that can discriminate whether an AI system generates a certain text (Jawahar et al., 2020). AI-generated context detection is useful in releasing texts that require strict censoring or originality such as official documents, consultation, and student submissions (Mitchell et al., 2023) to avoid abuse of AI systems. Further, a more critical and applicable field is to trace the origin of LLMs. While more and more companies and institutions are releasing their original LLMs, it is of great importance to trace whether an LLM is trained from a previous model, or is copied or distilled from another LLM. Since LLMs can produce massive generated data, future LLMs might be trained from these generated data, the human-written texts might be contaminated with different LLMs. Therefore, tracing the origin of the text is a major challenge in future LLM industries.

In this work, we first introduce the concept of origin tracing. Then we provide an effective tool named **Sniffer** and its evaluation benchmark to study the origin tracing problem. Origin tracing is to further categorize the origin of a given text. Specifically, we categorize the origins by the LLM abilities and by LLM service providers. We first trace the origin of GPT2 level LLMs such as GPT2 (Radford et al., 2019) from OpenAI, GPT-Neo/J (Black et al., 2021; Wang, 2021) from EleutherAI, we can also trace the GPT3 level LLMs such as text-davinci-003, ChatGPT (GPT3.5 turbo) (Brown et al., 2020), LLaMA (Touvron et al., 2023). With origin tracing, we can avoid AI abuse or potential model theft since the texts can be traced to a specific service

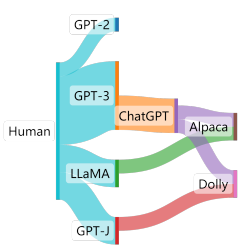


Figure 1: A knowledge flow of LLMs: with

[1] We are releasing all available resource at https://github.com//.

provider. While more and more companies and institutions are releasing their LLMs, origin tracing is the keystone of *anthropology* of LLMs. Then we introduce **Sniffer**, the first origin tracing tool. In Sniffer, we use contrastive features across open-source LLMs such as GPT2, GPT-Neo/J, and LLaMA. Specifically, we design heuristic features that capture the model-wise discrepancies which can help trace the origin of given texts. Then we utilize a simple linear classifier to project the extracted features to specific origins including known origins that have open-source models and unknown origins that are black boxes to users. The core motivation of the origin tracing tool Sniffer utilizes the discrepancies between LLMs as features to help trace the origins. Compared with previous methods, Sniffer utilizes model-wise features, which is different from supervised learning methods such as fine-tuning a RoBERTa (Liu et al., 2019) model; Furthermore, Sniffer is able to trace text origins and generalize to unknown origins, while previous methods that use model-wise features cannot.

With Sniffer, we further introduce a test dataset that contains collected texts from different origins as a benchmark to study the origin tracing problem. We provide plenty of experiments and through the experimental results, we have several non-trivial observations that help future LLM studies. In general, we find that: (1) we are able to trace the origins of generated texts when we can possess the models; (2) it grows harder to detect and trace origins when the LLMs are stronger; (3) LLM providers need to be more cautious as the origin of generated texts might be known only by the providers. (4) We can trace the origins of distilled LLMs such such as Alpaca and Dolly.

To summarize, in this paper, we: (1) raise the concern of origin tracing of AI-generated contexts; (2) build a tool to trace the origins of various open-source models by releasing a diversified benchmark for AI-generated contexts detection and origin tracing; (3) conduct various experiments to analyze the ability of LLMs when they are being traced and hope that future works can pay more attentions to the origin tracing of LLMs.

2 Related Work

Increasing Concern of LLM Security

Pre-trained models (Devlin et al., 2018; Radford et al., 2018, 2019; Raffel et al., 2020; OpenAI, 2023) are supposed to be harmless, harmful, and honest to users (Bai et al., 2022), however, there are various aspects that challenge LLM securities such as social bias, stereotypes, privacy leak or adversarial examples (Zhao et al., 2017; Carlini et al., 2020; Li et al., 2020).

Detection of AI-generated contexts is also a rapidly growing field that requires attention since the abuse of AI might be a major challenge in LLM applications (Bai et al., 2022). Still, current methods only consider detection as a binary task, that is, whether a given text is generated by an AI without considering tracing the origins of texts. Detection methods can be categorized into two lines:

Semantic-wise Detection

The most straightforward method to detect AI-generated contexts is to construct a text classification task (Zellers et al., 2019). Therefore, DetectGPT (Mitchell et al., 2023) introduces a strong RoBERTa-trained baseline that uses the dataset released by OpenAI [2] to train a classifier.

Model-wise Detection Unlike semantic-wise detection which discriminates the semantic difference between human-written and AI-generated texts, a more direct way is to explore the model-wise features. That is, AI-generated texts show discrepancies compared with humans when fed into AI models. These discrepancies are not easily noticed by humans as they might be a subtle difference that is possessed by a certain origin, therefore, many works focus on utilizing model-wise features such as log-likelyhood of model outputs, neural features, or bag-of-word features (Bakhtin et al., 2019; Solaiman et al., 2019; Gehrmann et al., 2019; Jawahar et al., 2020; Mitchell et al., 2023) to detect AI-generated contexts.

In the era of LLMs, there are similar works that work on using model-wise features of LLMs such as watermarking (Kirchenbauer et al., 2023), and backdoor plantings (Kurita et al., 2020; Li et al., 2021). In the computer vision field, model-wise features are also used in fake image detection (Dolhansky et al., 2020) but are less related to

[2] https://github.com/openai/gpt-2-output-dataset

Table 1: Different Detection Tools comparisons. Generalization ability represents how well white-box methods can detect texts generated from unknown models, therefore the supervised learning methods are not applicable in the generalization ability comparison.

Method	Model Access	Data Request	Generalization	Origin Tracing
$\log p(x)$	White-Box	Zero-Shot	Low	✗
DetectGPT	White-Box	Zero-Shot	Low	✗
Supervised-Learning	Black-Box	Full Data	N/A	✗
Sniffer	Black & White Box	Low-Resource	High	✓

LLM origin tracing due to the continuous nature of images.

3 Methods

We aim to detect whether a context is generated by an LLM system and trace the origin of the texts. Therefore, we design a simple method **Sniffer** [3] that is applicable in both white-box and black-box settings and only requires limited supervised data.

The core idea is to utilize the contrastive features between different accessible language models such as GPT-2, GPT-Neo, GPT-J, and LLaMA. We first obtain the perplexity of a target sample S based on different models denoted as $\theta_0, \theta_1, ..., \theta_N$, then we craft several heuristic features and construct a simple linear classifier to classify the origin of the given sample. Through such a feature engineering process, we can trace the origin of the target sample down to a known model θ_n, we can also generalize the contrastive features to show differences between unknown source models or human-written texts.

Compared with previous detection methods, as seen in Table 1, our proposed method is the first to allow origin tracing. Model-wise detection methods such as DetectGPT are designed to detect whether a text is generated by a certain model, which can not be well generalized to origin tracing.

3.1 Steps of Sniffer

The process of Sniffer includes: (1) Obtain and align token-level perplexity between different models; (2) Extract contrastive features; (3) Train features for origin tracing.

Obtain and Align Single Model Perplexity

Given target text S and a known model θ_n, we obtain the encoded tokens $\boldsymbol{x} = [x_0, x_1, ..., x_i, ...]$, the perplexity of i^{th} token x_i in text S given model θ_n is the log-likelyhood $ll_{\theta_n}(x_i) = \log p_{\theta_n}(x_i|x_{<i})$. Given a list of known models $\theta_0, \theta_1, ..., \theta_N$, we obtain a list of perplexities of the same text S. Since the tokenization process of each LLM might be different, we use a general word-level tokenization of S: $\boldsymbol{w} = [w_0, w_1, ...]$ and align calculated perplexities of tokens in $\boldsymbol{x}$ to the general words. If the word w is aligned to multiple tokens in $\boldsymbol{x}$, we use the averaged perplexity; if a token in $\boldsymbol{x}$ is aligned to multiple words, we assign these words with the same value. [4]. Further, the aligned perplexity is conditioned on the specific model-training process, therefore, the perplexity should be normalized for comparison between models. We apply normalization strategies including dataset-wise-normalization and L1-normalization for these aligned features. Dataset-wise normalization is to normalize the perplexity with an averaged perplexity on all data. Therefore, as seen in Figure 2, we obtain lists of word-level perplexities $ll_{\theta_n}(\boldsymbol{w})$ that are aligned across models.

Extract Contrastive Features

After obtaining aligned perplexities $ll_{\theta_n}(\boldsymbol{w})$, which is a list of token-wise perplexities, we aim to search features within the list of token-wise perplexities. Instead of introducing assumptions of the difference between human-written texts and machine-generated texts (Mitchell et al., 2023), the core idea of Sniffer is to find different features between models. Therefore, we pose a simple hypothesis:

Hypothesis 1 *A human written text tends to have a similar perplexity list across models, and a generated text tends to show discrepancy across models.*

To further generalize the extracted features for tracing unknown models, we pose another hypothesis:

Hypothesis 2 *The discrepancy of perplexity*

[3] This name is inspired by the fact the sniffer dogs are able to trace the scents that cannot be easily noticed by humans.

[4] The details of the aligning process can be seen in the Appendix.

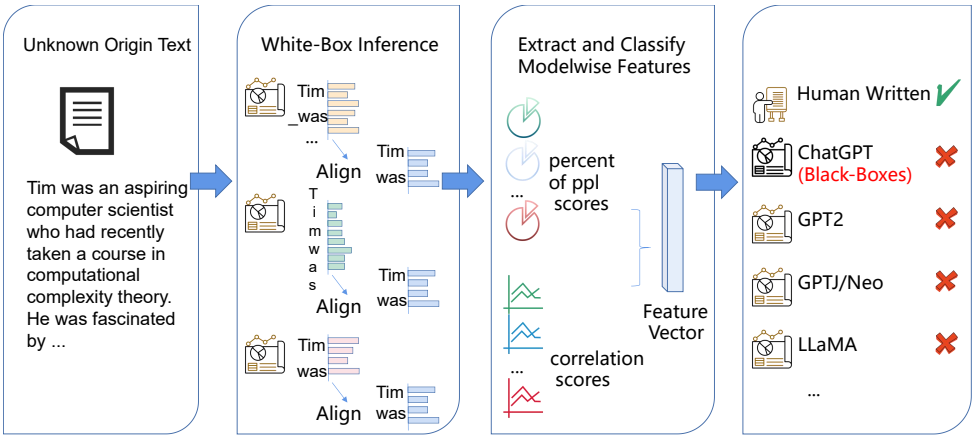


Figure 2: Sniffer process Illustration

curves across models can reveal features of both known and unknown models.

With these hypotheses, we can utilize the contrastive features between known models $\theta_0, \theta_1, ...$ to trace the origin of various models denoted as $\phi_0, \phi_1, ...$ that includes known and unknown models. Specifically, given a pair-wise known model comparison between modelθ_i and θ_j, we have $ll_{\theta_i}(\boldsymbol{w})$ and $ll_{\theta_j}(\boldsymbol{w})$ with aligned perplexities of L words in total. We first design a *percent-of-low-perplexity* score that calculates the percentage of the lower word perplexities of the perplexity of θ_i compared with θ_j: $\text{pct}_{ij} = \left(\sum_k^N \mathbb{1}\left(ll_{\theta_i}(w_k) < ll_{\theta_j}(w_k)\right)\right)/L$. Here, $\mathbb{1}(\cdot)$ is the indicator function that assigns 1 when the term is satisfied.

Given N known models, we have C_N^2 pairs and we can obtain C_N^2 pct_{ij} scores. We collect all these scores as heuristic features that can be used to trace the text origins. Plus, we also include the sentence-level perplexities and the Pearson and Spearman correlation coefficient between $ll_{\theta_i}(\boldsymbol{w})$ and $ll_{\theta_j}(\boldsymbol{w})$ to construct a feature vector as the final representation for origin tracing. For instance, given 4 known LLMs ($N = 4$), we have 4 sentence-level perplexity features, $C_4^2 = 6$ pct-scores, and $6 * 2 = 12$ correlation coefficient score, therefore the final representation vector is a 22-dim vector.

Train Features for Origin Tracing

After extracting the contrastive features from different known models, we can train a simple linear classifier $F(\cdot)$ to project the extracted features to different model origins. To train the classifier $F(\cdot)$, we collect a small amount of human-written texts that cover various aspects and use different known models to generate texts as similar or *parallel* data compared to human-written texts to train the linear classifier.

The trained classifier has several unique features:

(1) Low-resource required: Unlike semantic-wise classification tasks that require a large amount of data and a strong natural language encoder, after feature extraction, the final representation is a low-dimension vector, which requires only a small amount of data since the feature contains abundant model-wise heuristic knowledge for origin tracing;

(2) Generalization ability to unknown models and stronger LLMs: In the classifier studying process, we can collect unknown-model-generated texts to obtain their features based on known models and these features can reveal different traces compared with known models and human-written texts. Different from supervised-learning methods that rely on semantic-level features to detect text origins, model-wise features are **NOT** influenced as the quality of generated texts improves. That is, in the supervised learning methods, stronger LLMs are harder to detect since the generated texts are human-like, but model-wise features cannot be easily optimized.

(3) Extend Ability: In our proposed method, the linear classifier can be easily modified to trace various model origins. Given a new open-source model, we can easily use the feature extraction strategy above to re-train the classification model; given a new unknown model, we can easily collect a few generated texts and extract the features based on known models, and train a new classifier with the unknown model origin features to trace the new unknown origin. With such extended ability, our proposed method can be used in both black-box and white-box settings.

4 Experiments

4.1 Dataset Construction

In the origin tracing of LLMs, one major challenge is that LLMs are almost omniscient to world knowledge since they are trained with various and huge amounts of data. We collect a wide range of texts from different origins for the proposed origin tracing tool Sniffer to serve as a general detector.

We collect texts from domains including News articles, social media posts, web texts, scientific articles or academic papers, and technical documentation. We use public datasets including XSum dataset (Narayan et al., 2018) that contains news articles; IMDB dataset that contains social media reviews of movies; web texts (Radford et al., 2019) that contains texts from common-crawled online pages; PubMed and Arxiv dataset (Cohan et al., 2018) that contains academic topics; Wikipedia corpus used in SQuAD dataset (Rajpurkar et al., 2016) that contains general world knowledge. For each dataset, we randomly collect 1,000 documents and shuffle them into a human-written text dataset containing 6k documents. Then we generate AI-generated contexts from the texts we collected as *parallel* data to study origin tracing.

When generating texts from language models such as GPT-2, we use the first 10 words as the prompt to generate a document. When generating texts from instruction-tuned models such as GPT-3.5(text-davinci-003) and ChatGPT (turbo), we give several instructions including re-write instruction and story generation instruction to obtain a similar AI-generated text. (We show instruction details in the Appendix.) With these simple instructions, we collect AI-generated texts from instruction-tuned LLMs. For known origin models, we collect AI-generated texts from GPT2 (powered by OpenAI), GPT-J and GPT-Neo (powered by EleutherAI), LLaMA (powered by Meta AI). For unknown origin models, we collect AI-generated texts from GPT3.5-text-davinci-003, which is an instruction-tuned model with 175B parameters. Therefore, we collect 6k human written texts, and every 6k texts from GPT2, GPT-Neo, GPT-J, and 12k texts from GPT3 models, which is 36k texts in total. We divide the 36k texts into a train/test split with a 90%/10% partition.

We name the collected dataset **SnifferBench**, which can be further used in origin tracing and AI-generated contexts detection tasks. Further, the dataset collection process can be extended to different LLMs in the future with more different scenarios and prompts/instructions which further challenges the origin tracing ability.

4.2 Implementations of Sniffer

In Sniffer, we select several open-source (L)LMs as known models: we use GPT2-xl(1.5B), GPT-Neo(2.7B), GPT-J(6B) and LLaMA(7B) as known models. In the SnifferBench, we collect texts from origins including GPT2(OpenAI), GPT-Neo and GPT-J(EleutherAI), LLaMA (MetaAI), ChatGPT(GPT3.5-turbo from OpenAI), and human-written texts, therefore, the unknown origin is the ChatGPT(GPT3.5-turbo) model since they are not open-source models. The goal of origin tracing in Sniffer is to trace both known and unknown origins. We construct an inference server for each known model based on NVIDIA4090 GPUs and set the max sequence length given the maximum GPU allowance. We align all texts with a white-space tokenizer to obtain uniform tokenizations.

We utilize the aforementioned four known models and employ a linear classifier to construct a set of binary and multi-class Sniffers, used respectively for comparison with existing binary models like DetectGPT, and for origin tracing. In addition, we introduce a new variant of Sniffer: **Sniffer(+GPT3)**. As we are able to obtain logits of the generated texts in the GPT-3 API provided by OpenAI, we are able to treat GPT-3 model as a white-box model. Therefore, we collect a subset in the SnifferBench to test the origin tracing with GPT-3 models as white boxes. Therefore, in our implementation of Sniffer, we have 5 models in total which result in a 35-dimension vector in obtaining the sniffer feature. Here, we align the tokens with the tokenizer provided by OpenAI.

4.3 Metrics of Origin Tracing

In the SnifferBench, we collect texts from different origins, therefore, we calculate the precision and recall of each text origin tracing prediction. We can only calculate the known model and the human-written texts' precision and recall in baseline methods since these methods cannot be used in the origin tracing task.

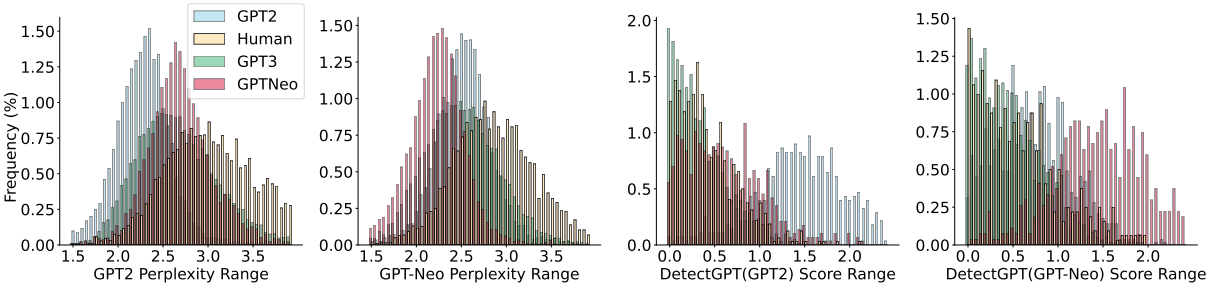


Figure 3: The discrepancy between different text origins in different baseline methods. In each figure, different bars show different text origins and each figure is to use a certain model of a certain detect method to test given texts.

Method	Different Text Origins					
	GPT-2			GPT-Neo		
	AI	Human	Overall	AI	Human	Overall
log $p(x)$	80.9/89.3	87.9/78.7	84.0	71.7/78.9	76.3/68.5	73.6
DetectGPT	88.9/88.9	89.9/90.2	89.5	74.4/79.3	80.0/75.5	77.2
Sniffer	**99.1/99.3**	**99.3/99.2**	**99.2**	**99.7/99.0**	**99.5/99.8**	**99.4**

Table 2: Precision/Recall Results of binary detection, we use macro-F1 as the overall metric. Since log$p(x)$ and DetectGPT methods are unable to trace different text origins, only the corresponding model-generated text and human-written text detection results are listed.

4.4 Results of Binary Detection

As we compare Sniffer with previous detection methods in the form of the methods, we construct experiments to explore how previous methods fail to run origin tracing.

We first implement log$p(x)$ method which is also used in the original GPTZero [5]; then we implement DetectGPT method which introduces a discrepancy score to discriminate AI-generated texts by adding multiple perturbations (we try 40 perturbations for each sample). We collect the sentence-level perplexity and the DetectGPT discrepancy score of the collected dataset based on a certain known model θ_n and draw a histogram showing the score distributions of different origin texts.

In Figure 3, we plot the histogram of the discrepancy between different texts' origins in log$p(x)$ and DetectGPT. In log$p(x)$, we plot the perplexity score of different text origins using a specific model such as GPT-2 or GPT-Neo, and in the DetectGPT method, we use the z-score proposed in DetectGPT. As seen in Figure 3, though there are multiple peaks showing that there are differences between different text origins, the overlap is too large to successfully separate different text origins. we can conclude that it is extremely difficult to discriminate text origins from log$p(x)$ features or z-score features. Therefore, it is important to introduce strong features to trace the texts' origins.

Since log$p(x)$ and DetectGPT methods are unable to trace different text origins, we only conduct the corresponding model-generated text and human-written text detection. Specifically, we select a threshold manually as the discrimination boundary in log$p(x)$ and DetectGPT. As listed in Table 2, even in the binary classification detection tasks they excel at, their performance still falls short of Sniffer. This further confirms that whether in origin tracing capability or binary classification detection ability, Sniffer is an exceptional method.

4.5 Results of Sniffer Origin Tracing

In Table 3, we can observe that Sniffer can obtain impressive results in tracing the text origins in the known models including GPT-2, GPT-J/Neo; further, when Sniffer does not use the GPT-3 models as white boxes, Sniffer can generalize to trace GPT-3 model origins and can properly discriminate them from human-written lines. Such an ability cannot be easily obtained as the GPT-3 models are stronger and similar to humans, meanwhile remaining unknown to the public.

Plus, we can observe that recently released LLaMA models are more difficult to trace, though it is a white box in Sniffer, indicating that stronger LLMs are harder to detect. When LLMs are being

[5] https://gptzero.me/

Method	Different Text Origins					
	GPT-2 (OpenAI)	GPT-J/Neo (EleutherAI)	LLama (Meta)	ChatGPT (OpenAI)	Human	Overall
Random	16.6/16.1	16.6/16.1	16.6/16.1	16.6/16.1	16.6/16.1	16.3
Sniffer	98.7/96.9	96.6/**98.0**	**85.0/84.3**	**77.7**/82.3	68.1/60.3	**84.8**
Sniffer (10%)	97.3/96.3	**96.7**/96.1	80.9/77.2	73.9/77.3	58.9/**67.7**	82.2
Sniffer (5%)	97.3/97.5	96.6/95.1	76.1/74.0	71.4/76.7	58.8/53.4	79.7
Sniffer (1%)	97.9/94.4	91.0/95.2	65.8/60.2	67.4/76.3	60.0/46.4	75.4
Sniffer (L1-norm)	97.8/**98.3**	**96.7**/95.9	75.2/74.4	74.7/82.4	**75.7**/62.4	83.3
Sniffer (log$p(x)$ only)	**98.9**/97.7	94.1/94.8	60.4/49.3	64.6/78.8	63.0/47.6	74.9
Sniffer (pct-score only)	98.3/96.6	94.0/94.8	59.5/53.2	60.0/79.9	58.3/26.8	72.1
Sniffer (log$p(x)$ + pct-score)	98.6/97.2	96.5/96.2	69.6/65.0	71.0/**82.5**	66.3/51.1	79.4

Table 3: Precision/Recall Results of Origin Tracing, we use macro-F1 as the overall metric. % in Sniffer is to train Sniffer with limited training data; log$p(x)$ and pct-score -only are the variants that only use the corresponding features for the linear projection.

Method	Different Text Origins					
	GPT-2 (OpenAI)	GPT-J/Neo (EleutherAI)	LLama (Meta)	GPT-3 (OpenAI)	Human	Overall
Sniffer(1%)	**93.8**/90.0	89.6/88.0	59.1/47.4	57.6/59.6	35.3/42.9	66.3
Sniffer(+GPT3)(1%)	92.0/**91.8**	**90.0/92.4**	**81.6/72.6**	**70.0/65.6**	**42.1/50.0**	**74.8**

Table 4: Results of Sniffer(+GPT3): We use GPT-3.5(text-davinci-003) to replace ChatGPT(turbo) since ChatGPT(turbo) does not provide logits.

studied by a wide range of researchers, it is also important to be alert that stronger models may be harder to detect, and harder to control which can cause potential harm to society.

4.6 Different Sniffers

Sniffer+GPT3

In Table 4, we list the results of using Sniffer(+GPT3) to trace the origins of texts generated by GPT3 models while we treat GPT3 models as white boxes. We use the OpenAI service that returns token logits therefore we use the text-davinci-003 model and test on a 1% dataset compared with the full dataset. Here, we replace texts generated from ChatGPT with davinci-003 outputs therefore the testset is different from the one used in tracing ChatGPT texts.

As seen, when the Sniffer feature can use GPT-3 logits, the results grow significantly higher compared with generalizing features from GPT2/J/Neo and LLaMA models to trace GPT-3. Therefore, we can conclude that although Sniffer is able to generalize its features to trace unknown origins, it is better to possess the LLMs, indicating that the actual LLM providers must be more cautious when releasing LLMs since they are more capable to avoid abuse or malicious usage of LLMs.

Limited Data Experiments

As we illustrated, in methods using model-wise features, we can use limited data to construct a powerful detector. Therefore, we use different numbers of training data to train Sniffer. As seen, when we use limited data to train the Sniffer model, the performances are not significantly harmed, indicating that the model-wise features are high-quality features that reveal obvious traces of texts for the origin tracing classification.

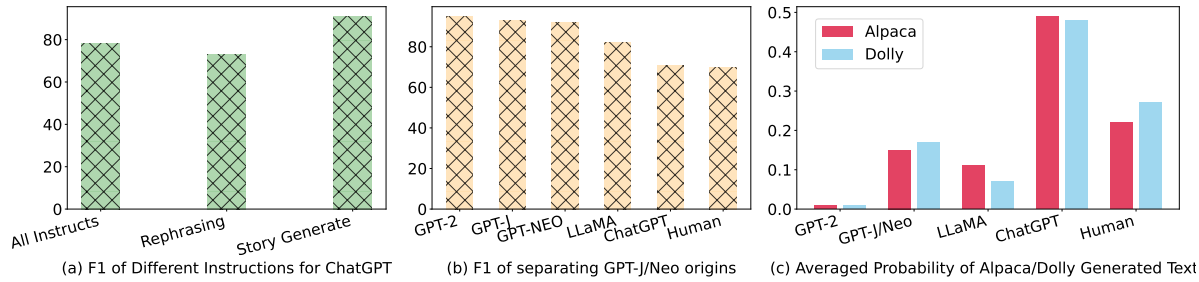
Feature Ablations

In the extracted features, we observe that using L1-norm can help obtain a higher performance in tracing human texts, but is rather weak in tracing different model origins, especially when tracing LLaMA. Therefore, we use datase-wise norm for the rest experiments.

To further analyze how the extracted features help trace the text origins, we run a simple ablation test that uses different features proposed in Sniffer. As seen in Table 3, the perplexity score log$p(x)$ is one key metric but can be significantly improved by the percent-of-perplexity score (pct-score), showing that we can trace text origins by analyzing the discrepancies between models when testing same texts as Sniffer did.

4.7 Difficulty of Tracing Different Types of Generated Texts

Generation Genre Influence



(a) F1 of Different Instructions for ChatGPT (b) F1 of separating GPT-J/Neo origins (c) Averaged Probability of Alpaca/Dolly Generated Text

Figure 4: Tracing different types of generated texts: (a) plots the ChatGPT tracing results that use different instructions; (b) plots the tracing results that separate GPT-J and GPT-Neo origins and calculate the f1-score of corresponding origins; (c) plots the tracing results that test Alpaca and Dolly models that use ChatGPT instructions to supervise fine-tuning the LLaMA/GPT-J models to build an instructed LLM.

As illustrated, we use several different instructions to instruct GPT3.5 (turbo) models and GPT3.5-text-davinci-003 models, we further discuss the tracing difficulty when the texts are generated by different instructions.

As seen in Figure 4(a), we find that when the texts are generated by rephrasing instructions, the texts are rather easy to trace while texts generated from a summary are harder to trace. Such an observation indicates that the difficulty of tracing texts generated by strong LLMs is also different when the instructions are different. The rephrased texts are more similar to human-written texts, therefore, are more difficult to detect.

Mixing Origin Tracing

In our origin tracing experiment setup, we divide GPT-J/Neo generated texts into the same origin since these models are provided by the same facility. That is, LLM origins can have different levels of classifications. As LLMs can be trained with *distill texts* from strong LLMs such as ChatGPT, it is harder to trace the origin if the model is trained based on a base model such as GPT-J or LLaMA but is instructed by ChatGPT-generated outputs. It is hard to tell whether the base model or the instruct model has a larger impact on the mixed-origin model. Therefore, we construct experiments to first separate GPT-J/Neo origins using the proposed datasets. Further, we test mixed-origin models such as Alpaca (Taori et al., 2023) (ChatGPT instructions tuned based on LLaMA) and Dolly [6] (ChatGPT instructions tuned based on GPT-J) by instructing these models to generate 400 samples and testing them with Sniffer.

In Figure 4(b), we show the f1-score of origin tracing that separates GPT-J and GPT-Neo models using the full data of SnifferBench. As seen, Sniffer is able to successfully divide GPT-J and GPT-Neo, indicating that the text origin divide can be of different levels. We can trace the text origins of a specific model or a certain party.

In Figure 4(c), we list the averaged probability of the Sniffer inference results of Alpaca and Dolly. As seen, texts from both Alpaca and Dolly tend to be categorized as ChatGPT-generated texts, indicating that the align process has a more significant impact on the generated texts compared with the base model. Therefore, Sniffer can be used as a detector for testing whether a model is trained from ChatGPT-generated instructions, helping protect the originality of LLMs.

5 Conclusion and Future Work

In this paper, we first introduce the concept of origin tracing, an important direction in the era of LLMs. Then we discuss two lines of AI-generated context detection and origin tracing methods and point out the necessity of studying model-wise features for origin tracing. We further design a simple Sniffer method as well as a benchmark to test the origin tracing challenge. Through extensive experiments, we find that the current origin tracing field is full of challenges including tracing texts from models with mixed origins; combining semantic features and model-wise features; and tracing texts from LLMs that are given various instructions. Therefore, we can hope for a continuous line of work that studies the origin tracing of LLMs and hopes to improve the trustworthy and safe usage of LLMs.

[6] https://huggingface.co/databricks/dolly-v2-12b

Limitations

Despite Sniffer having achieved substantial origin tracing results and unearthing many valuable insights, there are still some limitations:

(1) This study exclusively employs a simple linear classifier for origin tracing, without the utilization of more intricate models. This approach is adopted as we pioneer the application of model-wise perplexity features for origin tracing and AI-generated text detection, and it has proven sufficiently effective even on a linear classifier. Future research will explore the use of more complex models to enhance performance further.

(2) With more complicated model-generated texts, classifiers based on semantics can achieve better results. In the future, we plan to integrate Sniffer with semantic-wise models to experiment with more robust models.

As mentioned, we align tokens with different tokenization methods with a uniform tokenization strategy to compare the perplexity at the same level. As shown in Figure 6 in the Appendix, when the texts are tokenized by different tokenizers, we project different tokens to the byte level, and from the byte-level projections, we align different tokenized texts to a list of tokens with the same tokenizations.

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Table 5: Precision/Recall results of Chinese Dataset Performances of Origin Tracing.

Method	Different Text Origins						Human	Overall
	Wenzhong Fengshenbang	Damo Damo	Skytext SkyWork	ChatGLM THUDM	ChatGPT OpenAI	MOSS FudanNLP		
Sniffer	85.5/89.0	89.4/89.8	95.2/95.5	81.5/85.7	75.9/82.0	69.7/50.4	60.1/56.4	79.0

Table 6: Details of instructions used in Generating texts from ChatGPT, GPT3.5(text-davinci-003), Alpaca and Dolly models. In the story-generation, we use two instructs to obtain the generated document.

Instruction Type	Models	Instructions
Re-write	ChatGPT	You are an assistant that can rephrase the provided content. rephrase the following content: [document]
Story-Gen	ChatGPT	*Instruct 1:* You are an assistant that can summarize the provided content. summarize the following content: [document] *Instruct 2:* You are an assistant that can write a natural and fluent document based on the provided content, do not use fixed or academic writing style write a natural and fluent document like human based on the following content: [summary]
Re-write	GPT3.5	Rephrase the following content: [document]
Re-write	Alpaca & Dolly	Below is an instruction that describes a task, paired with an input that provides further context. Write a response that appropriately completes the request. ### Instruction: Rewrite the following paragraph in a different style using your own words. ### Input: [document]

A Appendix

Chinese Corpus Experiments

We also conducted a Chinese version of Sniffer as well as a collected testset for studying different types of LLMs.

We sample 1k samples from each open-source dataset of various domains including a long-document corpus of stories (Guan et al., 2022); various web texts from Iflytek classification dataset (Xu et al., 2020); Chinese academical documents from CSL dataset (Li et al., 2022); Chinese Wikipedia corpus from CMRC dataset (Cui et al., 2019); review corpus from Xiecheng APP [7]. We collect these datasets that cover various domains with relatively long documents (more than 200 Chinese characters per document). The dataset construction setup is similar to English dataset setups. We also use ChatGPT (GPT turbo) model to generate Chinese texts with the Chinese instructions as ChatGPT (GPT turbo) is a strong multi-lingual model.

As for open-source model selections, we adopt several open-source Chinese LLMs including the Wenzhong model (Zhang et al., 2022), a 2.7B GPT-2 style Chinese LLM; Damo model [8], another 2.7B GPT-2 style Chinese LLM; Skytext model [9], a 3B chatbot, and ChatGLM (Zeng et al., 2023), a 6B ChatGPT-style model trained with instructions.

For the generalization test of black-box models, we use ChatGPT (GPT turbo) and MOSS, a 16B Chinese LLM [10] with instructions that ask LLMs to re-write the given document as black-box origin tests.

We generate Chinese AI-generated contexts with open-source models and black-box models to build the whole Chinese benchmark for origin tracing tests.

As seen in Table 5, the Chinese texts show similar performances with English texts, indicating that the origin tracing strategy can be used in

[7] https://huggingface.co/datasets/seamew/ChnSentiCorp

[8] https://modelscope.cn/models/damo/nlp_gpt3_text-generation_2.7B/summary

[9] https://huggingface.co/SkyWork/SkyTextTiny

[10] https://github.com/OpenLMLab/MOSS

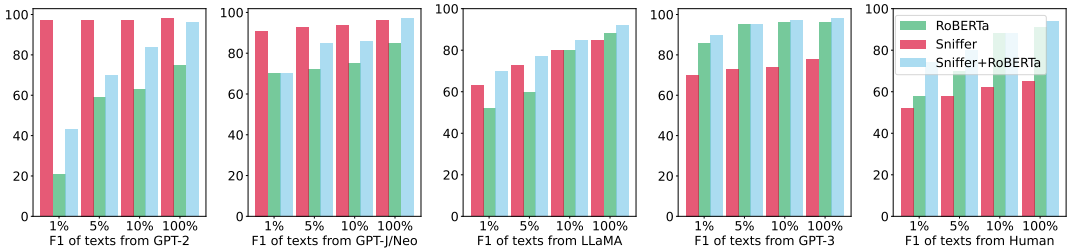


Figure 5: Comparison with Supervised Learning Methods that utilize semantic-wise features.

different languages.

Instruction Details

In table 6, we list the specific instructions used in LLMs. We consider simple instructions since we focus on studying the origin tracing of LLMs without further analyzing the working mechanisms and better usage of instructions, which we leave to future works.

Compare with Supervised Learning Methods

As discussed, the model-wise features trace the text origins by analyzing the model discrepancies, and the semantic-wise features are used as a fine-tuning task. We compare Sniffer with a fine-tuned RoBERTa model and measure the f1-score. Further, we combine Sniffer features and RoBERTa `[CLS]` feature to train a linear classifier as Sniffer+RoBERTa to test the performances of combinations of model-wise and semantic-wise features. As seen in Figure 5, the supervised learning method fails to solve the problem when the data is limited. Still, when the data is abundant, the performances are stronger than model-wise features (Mitchell et al., 2023; Souradip et al., 2023).

We need to notice that the supervised learning method fails to detect GPT-2/GPT-J/Neo generated texts, which is different from Sniffer results as GPT-2 texts are known to be less fluent compared with stronger models such as GPT-3 models. Therefore, we can assume that the RoBERTa models may capture some specific patterns since the GPT-3 generated texts only use several static instructions and the semantic features are easier to detect. The failure of GPT-2 detection indicates that semantic features are limited in origin tracing, calling for better algorithms to utilize model-wise features. In Sniffer+RoBERTa, we obtain promising results in tracing all origins, indicating that a proper combination of two types of features can help better trace text origins.

Case Studies

We list several case studies that are randomly selected from the testset. We show the texts to be detected, percent-of-perplexity scores, correlation scores calculated by Sniffer, and the tracing results.

As listed below, we show the list of perplexity scores of the given text and the extracted features, then we show the predicted tracing result. As seen, the perplexity list shows a similar trend between different models, but the perplexity value tends to show differences across models. For instance, in the GPT-2 generated text calculated list of perplexity, the GPT-2 perplexity is relatively lower than other perplexities calculated by other models, revealing the feature that helps trace the GPT-2 texts. On the other hand, for human-written texts, and texts generated by strong LLMs such as ChatGPT, the value does not show obvious differences between different models, for instance, some peaks in the perplexity list can be from the LLaMA models and some can be from some other models, which supports the hypothesis made above.

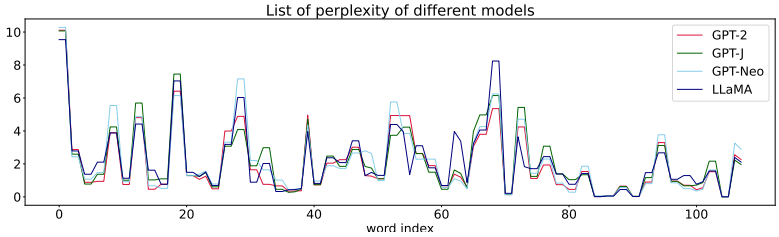
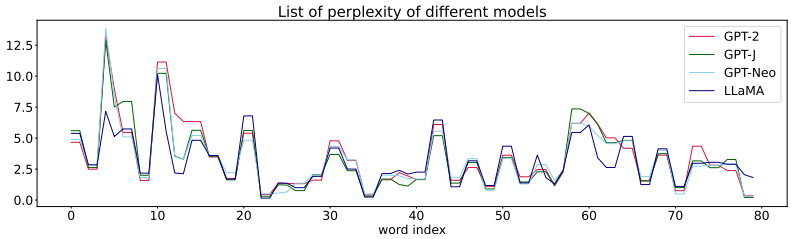
Text Origin	
GPT-2	I thought that Mukhsin has been wonderfully written. Its not a work of fiction, but it certainly feels like a novel. I agree that there is much to admire about, despite flaws, which will be evident to many of its readers.  Extracted Features: log $p(x)$ (GPT-2): 2.04 log $p(x)$ (GPT-Neo):2.18 log $p(x)$ (GPT-J): 2.18 log $p(x)$ (LLaMA): 2.21 pct-scores / Pearson scores / Spearman scores: GPT-2 and GPT-Neo 0.59/0.97/0.97 GPT-2 and GPT-J 0.57/0.96/0.95 GPT-2 and LLaMA 0.63/0.92/0.91 GPT-Neo and GPT-J 0.56/0.94/0.94 GPT-Neo and LLaMA 0.52/0.92/0.89 GPT-J and LLaMA 0.55/0.92/0.93 Tracing Results: GPT-2: 99.8 % GPT-J/Neo: 0.1 % LLaMA: 0.0% ChatGPT: 0.1 % Human: 0.0 %
GPT-Neo	Ten passengers on board the bus were reported to have either been injured, or have since been released from hospital. "This is an extremely rare occurrence," said an unnamed source at the scene. A second group of tourists were on the bus at the time of the incident but were not injured, according to reports.  Extracted Features: log $p(x)$ (GPT-2): 3.43 log $p(x)$ (GPT-Neo):3.21 log $p(x)$ (GPT-J): 3.23 log $p(x)$ (LLaMA): 3.08 pct-scores / Pearson scores / Spearman scores: GPT-2 and GPT-Neo 0.54/0.96/0.95 GPT-2 and GPT-J 0.40/0.95/0.95 GPT-2 and LLaMA 0.56/0.83/0.87 GPT-Neo and GPT-J 0.42/0.97/0.98 GPT-Neo and LLaMA 0.49/0.86/0.91 GPT-J and LLaMA 0.56/0.89/0.93 Tracing Results: GPT-2: 0.3% GPT-J/Neo: 72.6 % LLaMA: 3.0% ChatGPT: 18.3 % Human: 5.8 %

Table 7: Random selected case studies (a).

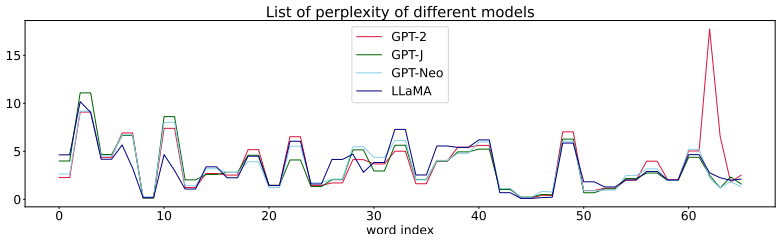
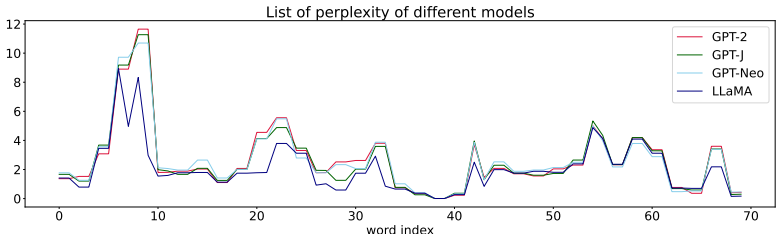
Text Origin	
GPT-J	He said ministers who disagreed with austerity measures could not go to other countries for talks as Germany would only make life difficult for them. And he said that he was a "proud German".  Extracted Features: log $p(x)$ (GPT-2): 3.86 log $p(x)$ (GPT-Neo):2.99 log $p(x)$ (GPT-J): 2.96 log $p(x)$ (LLaMA): 3.07 pct-scores / Pearson scores / Spearman scores: GPT-2 and GPT-Neo 0.65/0.70/0.90 GPT-2 and GPT-J 0.47/0.70/0.89 GPT-2 and LLaMA 0.44/0.65/0.85 GPT-Neo and GPT-J 0.44/0.96/0.98 GPT-Neo and LLaMA 0.50/0.86/0.90 GPT-J and LLaMA 0.56/0.85/0.89 Tracing Results: GPT-2: 0.0% GPT-J/Neo: 100.0 % LLaMA: 0.0% ChatGPT: 0.0 % Human: 0.0 %
LLaMA	This is a very memorable spaghetti western. It has a great storyline about two brothers, one a sheriff and the other a gunfighter. It is a very good one. I will recommend it to my friends.  Extracted Features: log $p(x)$ (GPT-2): 2.48 log $p(x)$ (GPT-Neo):2.46 log $p(x)$ (GPT-J): 2.42 log $p(x)$ (LLaMA): 1.91 pct-scores / Pearson scores / Spearman scores: GPT-2 and GPT-Neo 0.57/0.99/0.97 GPT-2 and GPT-J 0.56/0.99/0.95 GPT-2 and LLaMA 0.34/0.83/0.85 GPT-Neo and GPT-J 0.47/0.99/0.96 GPT-Neo and LLaMA 0.21/0.85/0.87 GPT-J and LLaMA 0.23/0.86/0.91 Tracing Results: GPT-2: 0.2 % GPT-J/Neo: 0.3 % LLaMA: 59.1 % ChatGPT: 31.3 % Human: 9.0 %

Table 8: Random selected case studies (b).

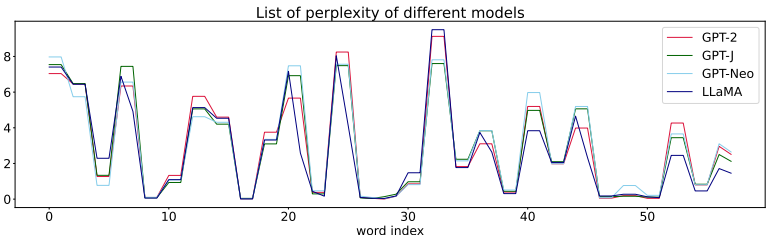
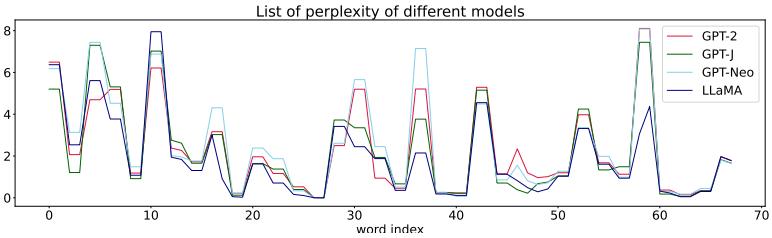
Text Origin	
Chat-GPT	The film in question focuses on the character played by the immensely talented Helena Bonham Carter, who delivered an impressive performance despite being confined to a wheelchair throughout the movie. 
	Extracted Features: log $p(x)$ (GPT-2): 2.73 log $p(x)$ (GPT-Neo):2.77 log $p(x)$ (GPT-J): 2.72 log $p(x)$ (LLaMA): 2.19
	pct-scores / Pearson scores / Spearman scores: GPT-2 and GPT-Neo 0.64/0.97/0.98 GPT-2 and GPT-J 0.55/0.98/0.98 GPT-2 and LLaMA 0.47/0.94/0.97 GPT-Neo and GPT-J 0.38/0.99/0.98 GPT-Neo and LLaMA 0.41/0.91/0.95 GPT-J and LLaMA 0.41/0.93/0.97
	Tracing Results: GPT-2: 0.8% GPT-J/Neo: 0.3 % LLaMA: 0.6 % ChatGPT: 97.3 % Human: 1.0 %
Human	College sports are also popular in southern California. The UCLA Bruins and the USC Trojans both field teams in NCAA Division I in the Pac-12 Conference, and there is a longtime rivalry between the schools. 
	Extracted Features: log $p(x)$ (GPT-2): 2.03 log $p(x)$ (GPT-Neo):2.21 log $p(x)$ (GPT-J): 1.95 log $p(x)$ (LLaMA): 1.74
	pct-scores / Pearson scores / Spearman scores: GPT-2 and GPT-Neo 0.59/0.95/0.95 GPT-2 and GPT-J 0.35/0.93/0.92 GPT-2 and LLaMA 0.21/0.85/0.92 GPT-Neo and GPT-J 0.41/0.93/0.95 GPT-Neo and LLaMA 0.22/0.84/0.94 GPT-J and LLaMA 0.26/0.91/0.94
	Tracing Results: GPT-2: 0.0 % GPT-J/Neo: 0.0 % LLaMA: 14.1% ChatGPT: 40.6 % Human: 45.3 %

Table 9: Random selected case studies (c).

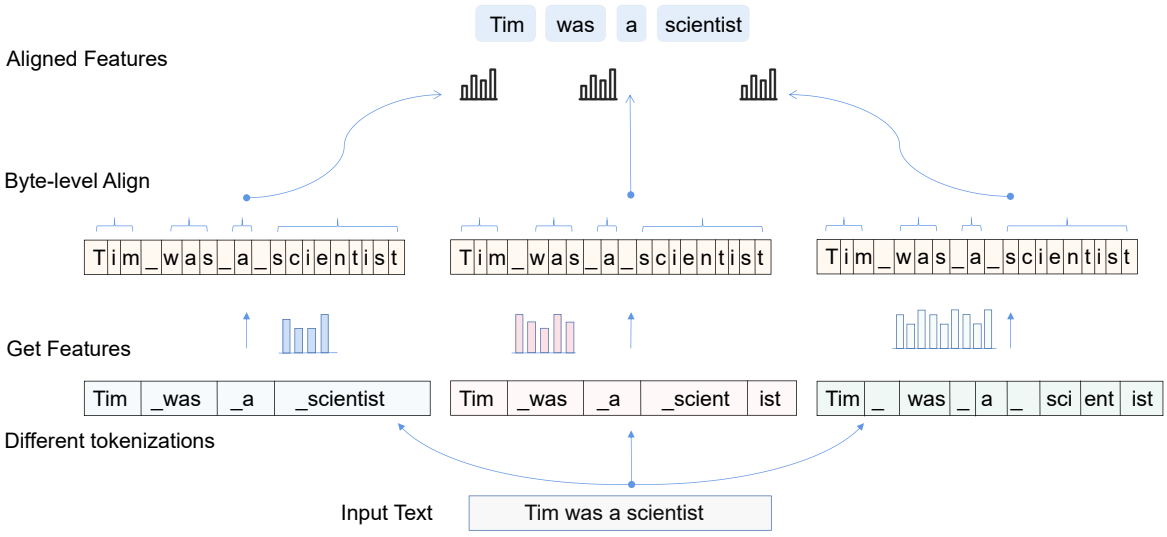


Figure 6: Align Strategies